Synopsis of the Ph.D thesis entitled

STUDY THE CLIMATE CHANGE IMPACT ON FUTURE IRRIGATION SCHEDULING BY CONSIDERING THE EXTREME CLIMATIC EVENTS

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Introduction

Climate change is a major global challenge, impacting agriculture, water resources, human health, and ecosystems. In regions like Aurangabad (19°–20°N, 74°–76°E), shifting from a semi-arid to arid climate has led to water scarcity and reduced agricultural productivity. Changing rainfall patterns and rising temperatures are increasing the frequency of extreme weather events like droughts, further straining water resources. This study focuses on Warud Kazi village from Aurangabad region, where tomato farming is a key economic activity. The village has already faced climate-related losses, such as the 2014 unseasonal rainfall that reduced tomato yields. This research aims to assess how future temperature and rainfall changes will affect water demand for tomato crops, helping farmers adapt to climate challenges. To predict future climate trends, Global Circulation Models (GCMs) provide large-scale climate data. However, since GCMs lack local detail, downscaling techniques are used to predict localized information from GCM. Two types of downscaling exist: Statistical downscaling, which utilizes historical climate data to establish relationships between local and GCM data, and Dynamic Downscaling, which relies on Regional Climate Models (RCMs). This study applies statistical downscaling to predict maximum temperature (Tmax), minimum temperature (Tmin), and precipitation for the Aurangabad region.

Two approaches were tested for downscaling:

1. Statistical Downscaling Model (SDSM)
2. Random Forest (Machine Learning Algorithm)

The study used CMIP5 GCM data under three Representative Concentration Pathways (RCPs): RCP 2.6, RCP 4.5, and RCP 8.5. The projections were compared with the baseline period (1961–2005) to analyze climatic changes. A trend detection analysis was conducted using three methods: Mann-Kendall Test, Sen's Slope Estimator, and Innovative Trend Analysis (ITA). Additionally, extreme climate events were detected by setting a 95th percentile threshold based on historical temperature and precipitation data. Any future values exceeding this threshold were classified as extreme events, helping predict future climate risks. The study then used CROPWAT software, developed by FAO, to analyze irrigation scheduling for tomato crops under extreme climate conditions.

Various research suggest FAO values are useful for irrigation modelling using CROPWAT, but this study compared them with site-specific data to assess accuracy. Very limited climate

and impact studies have been conducted in the Aurangabad region, with existing research primarily focusing on historical data and localized phenomena. Table 1 identifies different studies with some limitations:

Table 1: Identified Research Gaps in Climate Studies Conducted in or Near the Aurangabad Region

Sr. No.	Study By	Focus	Limitations
1	Masroor et al., 2022	Land use/land cover changes and their impact on historical climate patterns (urbanization effects on precipitation, soil moisture, and temperature).	Does not include future climate projections, which are crucial for assessing agricultural challenges.
2	Pande et al., 2023	Impact of urbanization on agriculture using historical data.	Lacks advanced modeling techniques and future climate projections, limiting its usefulness for long-term planning.
3	Pathan & Waikar, 2020b	Analysis of rainfall extremes.	Does not consider temperature trends and their impact on agricultural water requirements.
4	Pathan & Waikar, 2020a	Downscaling of climatic variables and their application to a specific sector.	Lacks short-year span analysis, considers only one downscaling method, and does not explore its application in agriculture.

Our research overcomes the limitations of previous studies by employing two downscaling techniques (SDSM and Random Forest), which provide a more comprehensive and accurate approach to future climate projections. We further enhance the study by incorporating finer temporal resolution analysis for future periods (2020s, 2050s, and 2080s) as well as for shorter year spans, offering more detailed insights into climate variability. Unlike prior research, which primarily focused on climate trends, we apply downscaled results to estimate future agricultural water requirements, filling a crucial gap in understanding the impacts of climate change on regional agriculture. Additionally, our use of advanced trend detection methods and the estimation of water requirements for tomato cultivation using CROPWAT strengthens our study, providing a robust, future-focused perspective on climate impacts and water resource management in semi-arid regions.

Objectives

1. Compare and evaluate the performance of two downscaling approaches (SDSM and Random Forest Algorithm) for projecting future climate trends and identifying extreme climatic events.
2. Conduct finer temporal resolution analysis for future periods (2020s, 2050s, 2080s) and shorter year spans.
3. Perform trend detection analysis using Mann-Kendall test, Sen's Slope Estimator and Innovative Trend Analysis (ITA) to identify significant temperature and precipitation trends.
4. Estimate future water needs and irrigation scheduling for tomato cultivation under extreme climatic events using downscaled projections.

Scope of Work

The scope of this study is to analyze climate impacts on agricultural water requirements for tomato cultivation in the Aurangabad region. It utilizes two downscaling techniques, Statistical Downscaling (SDSM) and Random Forest (RF), to project future temperature and precipitation trends under various RCPs for the 2020s, 2050s, and 2080s. The study focuses on the Aurangabad region, with specific attention to one selected village. Temporal analysis spans the near, mid, and long-term future, incorporating trend detection methods to identify significant climatic changes. Future water requirements for tomato cultivation are estimated using CROPWAT. The study aims to fill gaps in existing research by offering a comprehensive, future-oriented perspective on climate impacts and water resource management in semi-arid regions like Aurangabad.

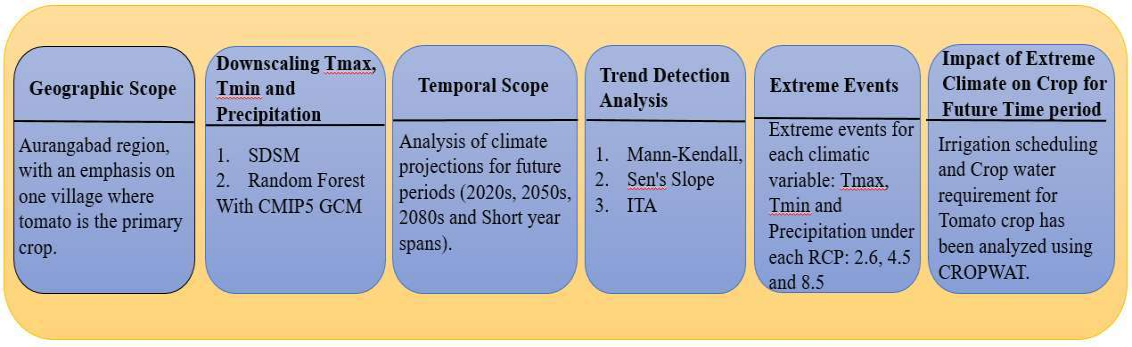

Geographic Scope
Aurangabad region, with an emphasis on one village where tomato is the primary crop.
Downscaling Tmax, Tmin and Precipitation
1. SDSM
2. Random Forest With CMIP5 GCM
Temporal Scope
Analysis of climate projections for future periods (2020s, 2050s, 2080s and Short year spans).
Trend Detection Analysis
1. Mann-Kendall,
2. Sen's Slope
3. ITA
Extreme Events
Extreme events for each climatic variable: Tmax, Tmin and Precipitation under each RCP: 2.6, 4.5 and 8.5
Impact of Extreme Climate on Crop for Future Time period
Irrigation scheduling and Crop water requirement for Tomato crop has been analyzed using CROPWAT.

Figure 1: Scope of work

Contribution made to the existing knowledge on the subject

This study contributes to existing knowledge by providing a comprehensive analysis of crop water requirements and irrigation scheduling under future extreme climate events in the Aurangabad region. It integrates four key components: (1) Comparative downscaling of climatic parameters using SDSM and Random Forest to identify the most suitable model, (2) Trend detection of climatic parameters to select the most reliable method, (3) Identification of extreme events based on downscaled data to assess future climate impacts, and (4) A comparative analysis of crop water requirements using CROPWAT, with inputs from both FAO standard values and regional site-specific data. This approach offers valuable, region-specific insights to address the challenges of future climate variability in the region.

Data Collection

To conduct the statistical downscaling analysis, observed daily temperature and precipitation values for the Aurangabad region were obtained from the Indian Meteorological Department (IMD) for the period 1961-2005. The corresponding large-scale climate variables required for the downscaling model were sourced from the CMIP5 (CanESM2) dataset available through the Climate Impact Scenarios site.

Methodology

- **Downscaling:**
  Two models, SDSM and Random Forest, were used to project future climate trends for Aurangabad using RCP scenarios 2.6, 4.5, and 8.5 from CMIP5 (CanESM2) GCM.

  1. SDSM: Involves data quality control, variable screening, model calibration, and result comparison.
  2. Random Forest: Includes feature ranking, data partitioning, training, and performance evaluation.

- **Climatic Variables Analysis:**
  SDSM model was calibrated for the period 1961–1980 and validated for 1981–2000, whereas downscaling by Random Forest was analysed using an 80/20 split . Projections for the 2020s, 2050s, and 2080s, and short spans (2006–2099) were analyzed.

❖ **Trend Detection:**

Mann-Kendall test, Sen's Slope Estimator, and ITA methods were used to detect climate trends (Tmax, Tmin, precipitation) under all RCPs.

❖ **Extreme Events:**

Extreme events were identified by setting a 95th percentile threshold from baseline data (1961–2005). Future climate data exceeding this threshold were classified as extreme.

❖ **Impact on Crop:**

The impact of extreme events on the tomato crop was evaluated using CROPWAT. CROPWAT requires three inputs: climate, crop, and soil data. A comparative approach was used for irrigation scheduling based on input parameters: Firstly, by site-specific data (collected from field studies, satellite observations, and WALMI records) and secondly by FAO standard values (from FAO Publication 56).

Results and Discussion

❖ **Downscaling Results for Tmax**

Maximum Temperature over Aurangabad regions has been downscaled using SDSM and Random Forest model. The results for selection of Predictors under SDSM and Random forest downscaling with scatter plot and feature ranking are as shown in figure 2 (a) and 2(b) respectively.

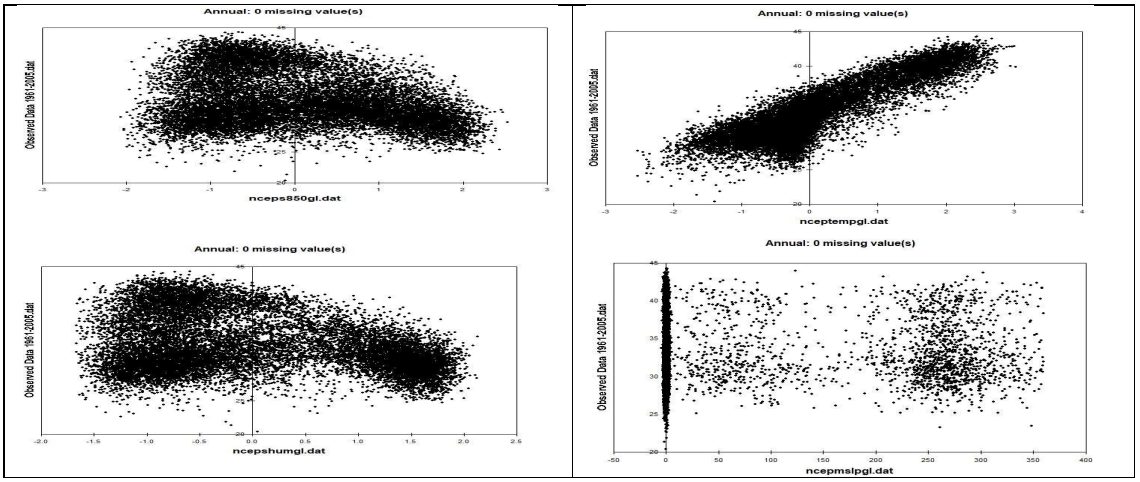


Figure 2(a) Scatter Plot between Predictors and Observed Tmax Over 1961-2005

Based on these scatter plots, we selected four key predictors: 1) ncepp850gl.dat (Specific humidity at 850 hPa), 2) ncepshumgl.dat (Surface specific humidity), 3) nceptempgl.dat (Mean temperature at 2m), and 4) ncepmslpgl.dat (Mean sea level pressure) for SDSM downscaling.

Feature Ranking:

	Predictor	Importance
24	P25	0.812493
22	P23	0.045678
23	P24	0.017669
16	P15	0.011347
6	P19	0.008763
5	P6	0.008268
10	P10	0.007823
13	P20	0.006755
17	P16	0.006202
1	P2	0.005894
21	P22	0.005877
18	P17	0.005803
4	P5	0.005035
3	P4	0.004914
2	P3	0.004914
19	P18	0.004722
9	P9	0.004707
14	P13	0.004488
7	P7	0.004485
12	P12	0.004373
15	P14	0.004184
8	P8	0.004167
0	P1	0.004049
20	P21	0.003801
11	P11	0.003588

Figure 2(b) Feature Ranking between Predictors and Observed Tmax Over 1961-2005

Based on the feature ranking results shown in Figure 2(b), the top three predictors with the highest importance were selected for the Random Forest downscaling process: 1) Mean temperature at 2 meters above the ground, 2) Global specific humidity values, and 3) Global specific humidity values at the 850 hPa pressure level. Following this selection, the SDSM model was calibrated for the period 1961-1980 and validated for 1981-2000. For the Random Forest model, an 80/20 data split was used for training and testing. The downscaled Tmax values from both models were compared with observed Tmax values during these periods, and the coefficient of determination (R^2) was calculated. The results for each model are provided in Table 2 (a) for SDSM, and Table 2 (b) for Random Forest, allowing for a comparative analysis of model performance.

Table 2 (a) Coefficient of Determination between Observed and Downscaled Tmax Values during Calibration and Validation period

Duration	R^2
1961-1980	0.99
1981-2000	0.99

Table 2 (b) Coefficients of Determination between Observed and Downscaled Tmax for Training and Testing Dataset

Duration	R^2
Training Dataset	0.98
Testing Dataset	0.86

Both tables show strong values of the coefficient of determination for the comparison of downscaled and observed Tmax. The SDSM model provides slightly better coefficient of determination values compared to the Random Forest model. The results from both downscaling models were analyzed for three future periods: 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099) under each RCP scenario. The downscaled annual monthly mean Tmax values for each future period were compared with the observed annual monthly

mean Tmax value of the baseline period, revealing an increase in temperature. The corresponding results for RCP 2.6 are presented in Table 3(a) for SDSM and Table 3(b) for the Random Forest model.

Table 3 (a) Increase in Tmax for Future Series With Respect to Baseline Period Under RCP 2. 6

Year	Increase in Tmax in ^{0}C
2011-2040	0.76
2041-2070	1.21
2071-2099	1.29

Table 3 (b) Increase in Tmax for Future Series With Respect to Baseline Period Under RCP 2. 6

Year	Increase in Tmax in ^{0}C
2011-2040	0.51
2041-2070	0.96
2071-2099	0.87

In both models, the Tmax values for the future periods show a continuous increase compared to the baseline period, with the rate of increase rising as the series progresses. The rate of increase in Tmax is higher in the SDSM downscaling model compared to the Random Forest model under RCP 2.6. Similarly, the results for the future periods under RCP 4.5 are presented in Table 4(a) for SDSM and Table 4(b) for the Random Forest model.

Table 4 (a) Increase in Tmax for Future Series With Respect to Baseline Period Under RCP 4.5

Year	Increase in Tmax in ^{0}C
2011-2040	1.05
2041-2070	1.64
2071-2099	2.06

Table 4 (b) Increase in Tmax for Future Series With Respect to Baseline Period Under RCP 4.5

Year	Increase in Tmax in ^{0}C
2011-2040	0.70
2041-2070	1.07
2071-2099	1.44

Table 4(a) and 4(b) show that under RCP 4.5, both models predict a higher increase in Tmax values for the future periods compared to the baseline period. The rate of increase is higher for both models under RCP 4.5 than under RCP 2.6. Additionally, the SDSM model predicts a greater increase in Tmax values compared to the Random Forest model across all three future periods under RCP 4.5. The results for the increase in Tmax values across the three future periods under RCP 8.5 are presented in Table 5(a) for SDSM and Table 5(b) for the Random Forest model.

Table 5 (a) Increase in Tmax for Future Series With Respect to Baseline Period Under RCP 8.5

Year	Increase in Tmax in ^{0}C
2011-2040	1.07
2041-2070	2.36
2071-2099	3.75

Table 5 (b) Increase in Tmax for Future Series With Respect to Baseline Period Under RCP 8.5

Year	Increase in Tmax in ^{0}C
2011-2040	0.56
2041-2070	1.57
2071-2099	2.46

The results in Table 5(a) and (b) indicate that under RCP 8.5, the SDSM model predicts a higher increase in Tmax values compared to the Random Forest model. However, the rate of increase in Tmax for all three future periods under both downscaling models is much more pronounced when compared to the results under the other two RCPs.

❖ **Analysis of Results for Short Year Spans for Tmax**

After analyzing the downscaling results across the three future periods, the downscaled Tmax values from both approaches were further evaluated for shorter time spans: 2006–2015, 2016–2025, 2026–2035, 2036–2045, 2046–2055, 2056–2065, 2066–2075, 2076–2085, 2086–2095, and 2096–2099. The annual monthly mean Tmax values for each short span were analyzed, and variations in Tmax were examined in detail for each period. The results of the Tmax analysis under SDSM and Random Forest are presented in Table 6(a) and Table 6(b), respectively under RCP 2.6.

Table 6(a) Tmax analysis over Short Span under RCP 2.6 for SDSM Results

Year Range	2006-2015	2016-2025	2026-2035	2036-2045	2046-2055	2056-2065	2066-2075	2076-2085	2086-2095	2096-2099
Annual monthly mean Tmax values in 0C	33.76	33.9	34.01	34.14	34.24	34.56	34.57	34.51	34.56	34.37

Table 6(b) Tmax analysis over Short Span under RCP 2.6 for Random Forest Results

Year Range	2006-2015	2016-2025	2026-2035	2036-2045	2046-2055	2056-2065	2066-2075	2076-2085	2086-2095	2096-2099
Annual monthly mean Tmax values in 0C	33.44	33.68	33.76	34.15	34.1	34.3	34.16	34.02	34.27	34.27

The analysis of short-span results under both downscaling techniques indicates an increase in the annual monthly mean Tmax values under RCP 2.6 compared to the baseline period, which is 33.27°C. According to the IPCC projections, under RCP 2.6, temperatures are expected to rise continuously until around 2099, after which a slight decline may occur. This trend aligns with the results of the SDSM downscaling model, whereas the Random Forest downscaling model suggests that Tmax values will remain constant during the last two short-year spans. In same way analysis of Tmax under RCP 4.5. For both the downscaling models have been shown in Table 7 (a) and Table 7 (b) respectively.

Table 7 (a) Tmax analysis over Short Span under RCP 4.5 for SDSM Results

Year Range	2006-2015	2016-2025	2026-2035	2036-2045	2046-2055	2056-2065	2066-2075	2076-2085	2086-2095	2096-2099
Annual monthly mean Tmax values in 0C	33.88	34.14	34.37	34.59	34.72	35.08	35.12	35.37	35.21	35.4

Table 7 (b) Tmax analysis over Short Span under RCP 4.5 for Random Forest Results

Year Range	2006-2015	2016-2025	2026-2035	2036-2045	2046-2055	2056-2065	2066-2075	2076-2085	2086-2095	2096-2099
Annual monthly mean Tmax values in 0C	33.78	33.96	34	34.14	34.27	34.52	34.71	34.74	34.58	34.73

The analysis of results for short spans under both downscaling techniques reveals an increase in annual monthly mean Tmax values under RCP 4.5 compared to the baseline period of 33.27°C. According to IPCC projections, the temperature trend under RCP 4.5 is expected to increase continuously up to 2099. As shown in Table 6(a), the SDSM results demonstrate a consistent rise in temperature values across all short spans. However, during the span of 2086–2095, a slight decrease in temperature is observed compared to the previous span, followed by an upward trend up to 2099. In contrast, the Random Forest results indicate an overall increase in temperature across short spans but show a slight decrease during 2086–2095 and again up to 2099. This deviation from the IPCC assumptions highlights slight inconsistencies in the Random Forest projections. Subsequently, the analysis of short-year spans under the RCP 8.5 scenario for both downscaling models is presented in Table 8(a) and Table 8(b).

Table 8 (a) Tmax analysis over Short Span under RCP 8.5 for SDSM Results

Year Range	2006-2015	2016-2025	2026-2035	2036-2045	2046-2055	2056-2065	2066-2075	2076-2085	2086-2095	2096-2099
Annual monthly mean Tmax values in 0C	33.86	34.1	34.56	34.76	35.15	35.91	36.18	36.85	37.2	37.47

Table 8 (b) Tmax analysis over Short Span under RCP 8.5 for Random Forest Results

Year Range	2006-2015	2016-2025	2026-2035	2036-2045	2046-2055	2056-2065	2066-2075	2076-2085	2086-2095	2096-2099
Annual monthly mean Tmax values in 0C	33.6	33.7	34.1	34.17	34.55	35.06	35.22	35.78	35.86	36.03

The analysis of short-year spans under both downscaling techniques for RCP 8.5 reveals a consistent rise in annual monthly mean temperature values for each time span compared to the baseline period. Both models align with the IPCC's assumption that, under RCP 8.5, temperature values will increase significantly at a rapid rate up to 2099.

❖ Trend Detection Analysis of Tmax

After completing the analysis of short-year spans, the trends in maximum temperature under each RCP for both downscaling models were examined using the Mann-Kendall test, Sen's Slope test, and Innovative Trend Analysis (ITA). Table 9 (a) and (b) present the trend analysis results for Tmax using the Mann-Kendall test and Sen's Slope test for the SDSM and Random Forest downscaling techniques, respectively.

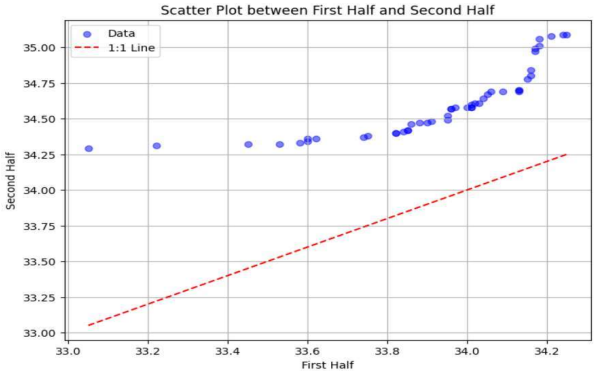
Table 9 (a): Trend Detection With SDSM Model

RCP	Mann-Kendall test (5% Significance)		Sen's slope Estimator
	Z statistic	P Value	B
RCP 2.6	13.23	0	0.0096
RCP 4.5	21.06	0	0.0178
RCP 8.5	50.92	0	0.0441

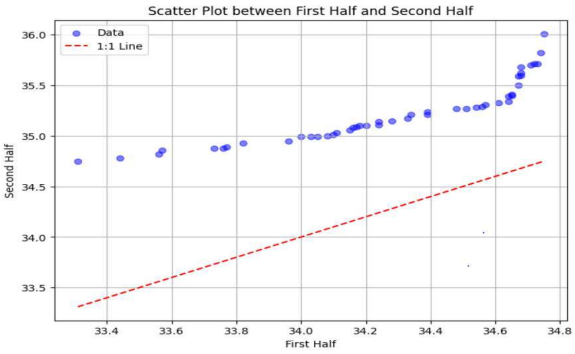
Table 9 (b): Trend Detection With Random Forest Model

RCP	Mann-Kendall test (5% Significance)		Sen's slope Estimator
	Z statistic	P Value	β
RCP 2.6	12.64	0	0.0077
RCP 4.5	16.62	0	0.0111
RCP 8.5	45.61	0	0.0317

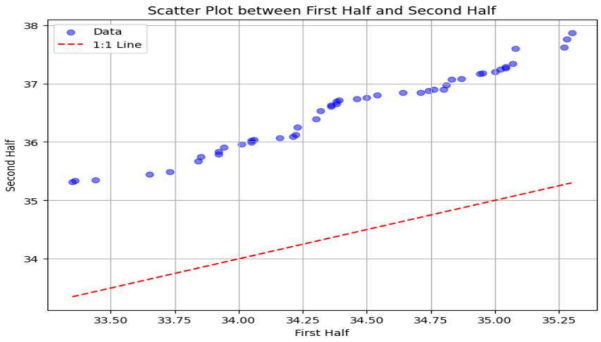
Tables 9 (a) and (b) both demonstrate an increasing temperature trend under each RCP. The Z-statistic value obtained from the SDSM downscaling is higher than that from the Random Forest model, indicating a stronger confirmation of the increasing Tmax trend in the SDSM results compared to the Random Forest results. The results obtained using the ITA technique for all RCPs under both downscaling methods are presented in Figure 3 (a) for SDSM and Figure 3 (b) for Random Forest.



Under RCP 2.6



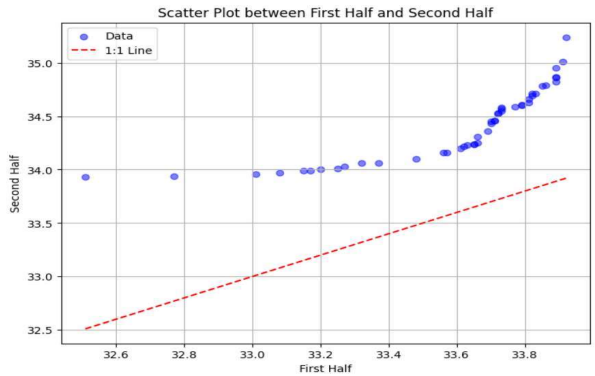
Under RCP 4.5



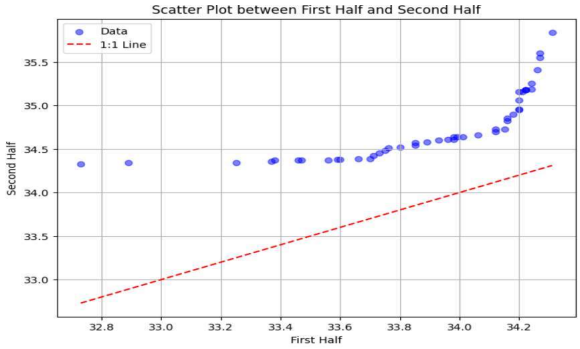
Under RCP 8.5

Figure 3 (a): Trend Detection analysis of Tmax using ITA for SDSM Model

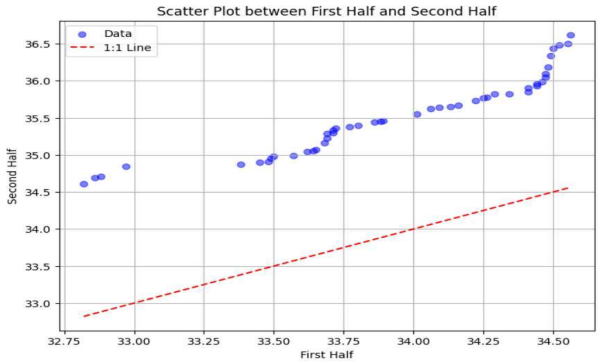
Figure 3 (a) shows a confirmed increase in Tmax values in the future under each RCP for the SDSM model. These trends align with the assumptions made by the IPCC regarding the rising temperature under different RCPs. Similarly, Figure 3 (b) below illustrates the increasing trend of Tmax under each RCP for the Random Forest model. However, under RCP 2.6, it shows a slight deviation from the IPCC assumptions, as the temperature values are expected to decrease near 2099, but this model predicts an increase. For RCP 4.5 and 8.5, the results align with the IPCC assumptions.



Under RCP 2.6



Under RCP 4.5



Under RCP 8.5

Figure 3 (b): Trend Detection analysis of Tmax using ITA for Random Forest Model

In a similar manner, the Minimum temperature (Tmin) was downscaled using both the SDSM and Random Forest models. Since SDSM provides a strong coefficient of determination between the observed and downscaled values, and its results align with the assumptions made by the IPCC, precipitation downscaling was also performed using the SDSM model. Both downscaling models show a good coefficient of determination for both the calibration and validation periods. However, similar to the Tmax results, the SDSM model provides a stronger coefficient of determination for the comparison of downscaled and observed Tmin values during both the calibration and validation periods, when compared to the Random Forest model.

❖ Analysis of Tmin for Future Series

The Tmin downscaling results were analyzed similarly to Tmax. Tmin showed a continuous increase across the 2020s, 2050s, and 2080s compared to the baseline (1961–2005) under all RCP scenarios (2.6, 4.5, and 8.5). As with Tmax, SDSM projected a higher increase in Tmin than the Random Forest model across all future periods.

❖ **Analysis of Tmin for Short Year Span**

After analyzing the future series, Tmin was examined over short year spans (2006–2099). The SDSM model shows a continuous rise in Tmin from the baseline (19.44°C), with stabilization under RCP 2.6 in the last two spans (2086–2099). Under RCP 4.5, Tmin increases steadily, except for a slight deviation in 2086–2095, while RCP 8.5 shows a sharp, uninterrupted rise. The Random Forest model also indicates a Tmin increase, though it slightly declines near 2099. Tmin rises continuously under RCP 4.5 and 8.5, with the highest increase observed in RCP 8.5.

❖ **Trend Detection Analysis for Tmin**

Tmin trends were analyzed using the Mann-Kendall, Sen's Slope, and ITA tests for both SDSM and Random Forest downscaling methods, similar to Tmax. For Random Forest, the Mann-Kendall test shows no trend under RCP 2.6, while Sen's Slope and ITA indicate an increasing trend. Under RCP 4.5 and 8.5, all three techniques consistently show an increasing trend. Previous studies suggest Tmin is expected to rise, supporting the accusracy of Sen's Slope and ITA results, which align with the short-year span analysis. For SDSM downscaling, all three techniques confirm an increasing Tmin trend under each RCP, consistent with short-year span findings. As noted earlier, SDSM results align better with IPCC assumptions and show higher calibration and validation accuracy than Random Forest. Due to its superior performance, SDSM was also used for precipitation downscaling. After successful calibration and validation, future precipitation trends were analyzed.

❖ **Analysis of Precipitation for Future Series**

After calibration and validation, SDSM performed better and its Tmax projections for future series aligned with IPCC trends compared to the results of Random Forest. Therefore, SDSM was used to downscale precipitation. Similar to Tmax and Tmin, the downscaled precipitation values were analyzed for three future periods: the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099). The annual monthly mean precipitation for each future period was compared with the baseline period's annual monthly mean precipitation. All future periods indicate an increase in precipitation, with the increase found to be nearly consistent across the last two future periods.

❖ **Analysis of Precipitation for Short Year Span**

For each RCP, the SDSM model shows an increase in annual monthly mean precipitation values compared to the baseline period (1961–2005).

❖ **Trend Detection Analysis of Precipitation**

Similar to Tmax and Tmin, precipitation trends were analyzed using three techniques: the Mann-Kendall test, Sen's Slope test, and ITA test. The downscaling results under RCP 2.6 indicate a decreasing trend in precipitation according to the Mann-Kendall and Sen's Slope tests, while the ITA test shows an increasing trend. Under RCP 4.5, the downscaling results indicate no trend according to the Mann-Kendall test, while both the Sen's Slope test and ITA test show an increasing trend. Under RCP 8.5, all three tests indicate an increasing trend in the downscaled precipitation values.

❖ **Extreme Events for Tmax, Tmin and Precipitation**

Extreme events were identified in the future time series for Tmax, Tmin, and precipitation. The 95th percentile of annual monthly mean temperatures and precipitation from the baseline period (1961–2005) served as the reference threshold for detecting these events. Any annual monthly mean temperature or precipitation value exceeding this threshold in the future was classified as an extreme event. This analysis was conducted for both downscaling techniques under each RCP scenario. The data from these extreme events were then used as input for the CROPWAT software to assess their impact on crop water requirements and irrigation scheduling. Since CROPWAT requires all three parameters as input, common years from the extreme climate events for all three variables were identified, and the RCP wise list is provided in Table 10

Table 10: Extreme Event Years

RCP	Extreme Event Years
RCP 2.6	2046,2050,2059,2060,2079
RCP 4.5	2016, 2039, 2060, 2061, 2063, 2071, 2078, 2084, 2093
RCP 8.5	2053, 2062, 2070, 2072, 2074, 2076, 2081, 2082, 2088, 2090

The extreme event years, shown in Table 10, were used for the crop water requirement analysis.

❖ **Crop Water Requirement and Irrigation Scheduling by CROPWAT**

We aimed to study the impact of extreme climatic events on crop water requirements and irrigation scheduling. For this study, the tomato crop was considered. The CROPWAT software was run twice for each extreme year: first using input data based on field observations and government department records, and second using standard values provided by FAO. The results of the crop water requirement from both methods were compared with the average values used for tomato crops, as provided by FAO and the Water and Land Management Institute (WALMI) in Aurangabad. Based on this comparison, the analysis was conducted.

Using the two approaches, the crop water requirement (in mm) for the entire duration of the crop is provided in Table 11 and Table 12. These table presents the data year-wise and RCP-wise**.**

Table 11: Crop Water Requirement in mm using First Approach

RCP	Extreme Year	CWR (mm)
RCP 2. 6	2046	826.1
	2050	850.3
	2059	820.5
	2060	811.8
	2079	796.5
RCP 4.5	2039	756.3
	2060	768.7
	2061	765.9
	2063	789.1
	2071	793.7
	2078	798.0
	2084	779.0
	2093	770.0
RCP 8.5	2053	784.1
	2062	786.4
	2070	778.6
	2072	804.3
	2074	781.6
	2076	806.5
	2081	802.8
	2082	816.2
	2088	829.9
	2090	818.5

Table 12: Crop Water Requirement in mm using Second Approach

RCP	Extreme Year	CWR (mm)
RCP 2. 6	2046	731.5
	2050	752.7
	2059	727.5
	2060	719.0
	2079	705.1
RCP 4.5	2039	673.3
	2060	683.9
	2061	680.5
	2063	701.0
	2071	704.5
	2078	708.5
	2084	691.8
	2093	683.5
RCP 8.5	2053	697.2
	2062	698.4
	2070	692.5
	2072	715.3
	2074	694.0
	2076	716.5
	2081	714.2
	2082	724.5
	2088	735.3
	2090	727.9

In the first approach to estimating crop water requirements, we considered all extreme events for maximum temperature, minimum temperature, and precipitation, as downscaled in this study. Crop data was obtained from WALMI, while soil data was collected from field

observations and satellite imagery using Google Earth Engine. The results for crop water requirements under this approach are presented in Table 11. According to FAO and WALMI Publication No. 21, the average water use for tomato crops is generally 700 mm. However, as shown in Table 11, the crop water requirement in each year exceeds 700 mm. This is because extreme temperature and precipitation events were considered in the analysis. Farmers from Warud Kazi village, with whom we discussed the cropping timeline, indicated that tomato cultivation begins in June, coinciding with the onset of the monsoon in India. Despite this, the water requirement exceeds the average value, likely due to the influence of extreme climatic events. In seasons with less precipitation, this value could increase further. For the given time span and under each RCP scenario, the crop water requirement remains higher than the average. In the second approach, we also considered extreme climatic events for maximum temperature, minimum temperature, and precipitation, as downscaled in this study. However, crop and soil data were sourced from FAO Publication 56, which provides generalized values based on crop and soil type. The results of crop water requirements under this approach are presented in Table 12. Similar to the first approach, higher water requirement values are observed under each RCP scenario. However, in some extreme years, values less than 700 mm are noted. This may be due to the generalized nature of the FAO soil data, which might not capture localized soil characteristics as accurately as field-based data. Nevertheless, the majority of the values under each RCP exceed the average water requirement of 700 mm. It is important to note that in both Table 11 and Table 12, the crop water requirement does not show a continuous increase over time. This is because, while the trends for Tmax, Tmin, and precipitation indicate an overall increasing pattern relative to the baseline period, deviations are observed. These deviations, particularly in precipitation, contribute to the variability in crop water requirements across different time spans. Despite this variability, we can adopt the first approach for crop water requirement calculation, as it incorporates more localized data and aligns well with extreme climatic events. Ultimately, under the first approach, an increasing crop water requirement is observed under each RCP scenario, underscoring the significant impact of climate change on water needs for tomato crops. After analyzing the crop water requirement, irrigation schedules were predicted based on the total duration of the crop, which is generally 135 days. For this study, we considered June 2nd as the starting date for planting the crop. From this date onwards, up to the crop's full duration, CROPWAT was used to determine when and how much water should be provided to the crop, measured in millimeters. This calculation was based on crop and soil data, along with the precipitation available during that period. CROPWAT divided the irrigation schedule into the crop’s growth stages: initial, development, mid, and late. For each

extreme year, the model was successfully executed, providing irrigation schedules specific to the conditions of that year. A sample result of the irrigation schedule is shown in Figure 4.

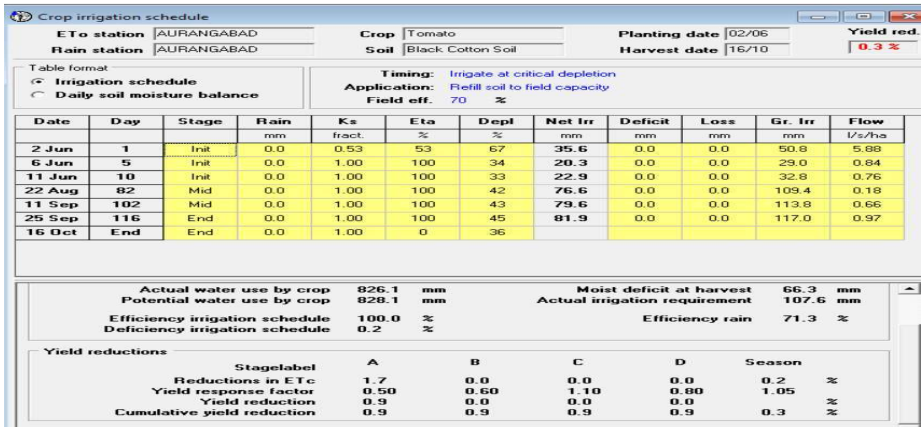

Crop irrigation schedule
ETo station AURANGABAD
Rain station AURANGABAD
Crop Tomato
Soil Black Cotton Soil
Planting date 02/06
Harvest date 16/10
Yield red. 0.3 %
Table format
Irrigation schedule
Daily soil moisture balance
Timing: Irrigate at critical depletion
Application: Refill soil to field capacity
Field eff. 70 %
Date Day Stage Rain Ks Eta Depl Net Irr Deficit Loss Gr. Irr Flow
mm fract. % % mm mm mm mm l/s/ha
2 Jun 1 Init 0.0 0.53 53 67 35.6 0.0 0.0 50.8 5.88
6 Jun 5 Init 0.0 1.00 100 34 20.3 0.0 0.0 29.0 0.84
11 Jun 10 Init 0.0 1.00 100 33 22.9 0.0 0.0 32.8 0.76
22 Aug 82 Mid 0.0 1.00 100 42 76.6 0.0 0.0 109.4 0.18
11 Sep 102 Mid 0.0 1.00 100 43 79.6 0.0 0.0 113.8 0.66
25 Sep 116 End 0.0 1.00 100 45 81.9 0.0 0.0 117.0 0.97
16 Oct End End 0.0 1.00 0 36
Actual water use by crop 826.1 mm
Potential water use by crop 828.1 mm
Efficiency irrigation schedule 100.0 %
Deficiency irrigation schedule 0.2 %
Moist deficit at harvest 66.3 mm
Actual irrigation requirement 107.6 mm
Efficiency rain 71.3 %
Yield reductions
Stagelabel A B C D Season
Reductions in ETc 1.7 0.0 0.0 0.0 0.2 %
Yield response factor 0.50 0.60 1.10 0.80 1.05
Yield reduction 0.9 0.0 0.0 0.0 %
Cumulative yield reduction 0.9 0.9 0.9 0.9 0.3 %

Figure 4: Irrigation Scheduling using CROPWAT

As shown in Figure 4, irrigation scheduling for each extreme year was analyzed using the CROPWAT software to determine the amount of water required by the crop at each stage of its growth.

Principal Conclusion

- Comparison of Downscaling Techniques (SDSM vs. Random Forest)
  1) The study compared the performance of SDSM and Random Forest for downscaling climate variables.
  2) SDSM performed slightly better than Random Forest, primarily due to its higher coefficient of determination during calibration and validation.
  3) Tmax trends from SDSM downscaling aligned more closely with IPCC's future projections compared to those from Random Forest.
  4) While Random Forest also demonstrated good performance, SDSM was found to be more reliable for downscaling climatic parameters.

- Finer Temporal Resolution Analysis for Future Periods
  1) Future climate projections were analyzed for three time periods: 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2099).
  2) It was observed that SDSM predicted higher temperature and precipitation values compared to Random Forest across all time periods.

- Trend Detection Analysis for Temperature and Precipitation
  1) Trend detection was performed using Mann-Kendall, Sen's Slope, and ITA to assess significant trends.
  2) ITA consistently detected increasing trends in Tmax, Tmin, and precipitation under all RCP scenarios.
  3) The results aligned with previous studies in the region, reinforcing ITA as a reliable and straightforward method for climatic trend assessment.

- Estimation of Future Water Requirements & Irrigation Scheduling
  1) Downscaling results were utilized to identify extreme climate events, which were then analyzed for their impact on crop water requirements.
  2) CROPWAT software was used to estimate water requirements for tomato cultivation using two approaches:
     a) Extreme event data combined with Site-specific data (collected from field studies, satellite observations, and WALMI records)
     b) Extreme event data combined with standard FAO input values.
  3) Both approaches indicated that crop water requirements under all RCPs exceeded the FAO's standard requirement of 700 mm.
  4) The first approach (field observations) consistently showed higher water requirements, suggesting that tomato cultivation will demand significantly more water under extreme climatic conditions. Since this approach incorporates real field data, it is considered more reliable for estimating future irrigation requirements.
  5) Irrigation scheduling was successfully completed, detailing water requirements for different growth stages of tomato to optimize water use.

Publications

Conferences

1. Barokar Y.J. and Pradhan V.S., "Assessment of Maximum Temperature for Future Time Series over Aurangabad City,Maharashtra State India", International conference on Environmental Sustainability (ICES2023) Organised by **VJTI**, 16th to 17th March 2023 **(Presented).**
2. Barokar Y.J. and Pradhan V.S. , "Assessment of Maximum Temperature for Future Time Series over Maharashtra State India", 28th International Conference on Hydraulics, Water Resources, River and Coastal Engineering, Organized by **NIT Warangal** 20 to 22 Dec.2023 **(Presented).**

3. Barokar Y.J. and Pradhan V.S. , "Future Projections and Trend Analysis of Minimum Temperature Over Maharashtra Using SDSM and CMIP5 Models", International Conference on Sustainable Energy and Environment (ICSEE) 2025 Organised by **BITS Pilani**, GOA, 8th to 10th March 2025 **(Acceptance Received).**

Journals

1. Barokar Y.J. and Pradhan V.S., "Assessment of Maximum Temperature for Future Time Series over Aurangabad City, Maharashtra State India", Research Journal of Chemistry and Environment, World Research Association, Vol. 28(11); 37-47, Nov. 2024. https://doi.org/10.25303/2811rjce037047 **(Published, Scopus and NAAS indexed)**

2. Barokar Y.J. and Pradhan V.S., "Downscaling CMIP5 Tmin Projections with Random Forest: A Study on Aurangabad Region, Maharashtra State India", Journal of Indian Water Work Association, Vol. 56, July-September 2024, Issue No. 3 **(Published, UGC Care-I indexed)**

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4. Barokar Y.J. and Pradhan V.S., "Comparative Analysis of Statistical Downscaling and Trend Detection Techniques for Predicting Temperature Trends: A Case Study of the Aurangabad Region", Green Technologies and Sustainability **(In Review Process)**

Book Chapter

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